The structmcmc package: Structural inference of Bayesian networks using MCMC

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I will describe the **structmcmc** package, which implements the widely-used MC^3 algorithm (Madigan et al., 1994), as well as a number of variants of the algorithm. The MC^3 algorithm is a Metropolis-Hastings sampler for which the target distribution is the posterior distribution of Bayesian networks.

The implementation allows the local conditional distributions to be multinomial or Gaussian, using standard priors. Arbitrary structural priors for the Bayesian network can be specified. The main difficulty in sampling Bayesian networks efficiently is ensuring the acyclicity constraint is not violated. The package implements the cycle-checking methods introduced by King and Sagert (2002), which is an alternative to the method introduced by Giudici and Castelo (2003). To enable convergence to be assessed, a number of tools for creating diagnostic plots are included.

Interfaces to a number of other *R* packages for Bayesian networks are available, including **deal** (hill-climbing and heuristic search), **bnlearn** (a number of constraint-based and score-based algorithms) and **pcalg** (PC-algorithm). An interface to **gRain** is also included to allow its probability propagation routines to be used easily.

References

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